Chapter

Tackling the Risk of Stranded Electricity Assets with Machine Learning and Artificial Intelligence

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Abstract

The Paris Agreement on climate change requires nations to keep the global temperature within the 2°C carbon budget. Achieving this temperature target means stranding more than 80% of all proven fossil energy reserves as well as resulting in investments in such resources becoming stranded assets. At the implementation level, governments are experiencing technical, economic, and legal challenges in transitioning their economies to meet the 2°C temperature commitment through the nationally determined contributions (NDCs), let alone striving for the 1.5°C carbon budget, which translates into greenhouse gas emissions (GHG) gap. This chapter focuses on tackling the risks of stranded electricity assets using machine learning and artificial intelligence technologies. Stranded assets are not new in the energy sector; the physical impacts of climate change and the transition to a low-carbon economy have generally rendered redundant or obsolete electricity generation and storage assets. Low-carbon electricity systems, which come in variable and controllable forms, are essential to mitigating climate change. These systems present distinct opportunities for machine learning and artificial intelligence-powered techniques. This chapter considers the background to these issues. It discusses the asset stranding discourse and its implications to the energy sector and related infrastructure. The chapter concludes by outlining an interdisciplinary research agenda for mitigating the risks of stranded assets in electricity investments.

Keywords: stranded assets, stranded resources, unburnable carbon, machine learning, artificial intelligence, carbon budgets, derisking investments, climate change

1. Introduction

The power industry is in transition, and energy management systems are adapting to it. Recently, the rapid proliferation of distributed energy resources (DERs) (e.g., distributed generation such as residential solar photovoltaics (PV) and wind electricity, controllable loads, and energy storage), have transformed operational, planning, and regulatory dynamics. Low-cost natural gas in the US, Europe, and elsewhere continues to push gas-fired electricity generation to the top of the generation mix. To this end, governments continue to promote low-carbon technologies through ever-stringent energy policies, like renewable portfolio standards (RPS), net metering, feed-in tariffs, and carbon pricing initiatives and emission trading schemes like the European Union Emission Trading System (EU ETS), Switzerland Emissions Trading Scheme, emissions trading schemes in China and Australia, the Regional Greenhouse Gas Initiative (RGGI) in the nine U.S. states in the Northeast and Mid-Atlantic region, the Transportation and Climate Initiative (TCI) under consideration for transportation emissions in the Northeast and Mid-Atlantic, the California and Quebec's Western Climate Initiative, among others. Furthermore, this growth in renewable electricity generation has been motivated by customers' preference for distributed energy as a means to fostering grid reliability and system efficiency, cost reduction, and improved customer choice over their power supplies [1–3].

These efforts are in line with the 2015 Paris Agreement on climate change and its nationally determined contributions' (NDCs) long-term goal of keeping the rise in global mean temperature to "well below [two degrees Celsius (2°C)] above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels" [4]. Moreover, limiting these temperature targets requires reaching net-zero global carbon dioxide (CO_2) emissions "between 2060 and 2070," with full decarbonization or "net negative CO_2 emissions" realized before the end of the century [5]. From a policy perspective, this transition from carbon-intensive sources to low and non-carbon-emitting sources is continuing as high penetrations of distributed electricity, energy storage and management devices, and investment in new forms of flexible demand resources become connected to the power grid network. Such significant shifts threaten the fossil energy business model and could, in turn, result in the "stranding" of the carbon-intensive assets through retirement or devaluation [6–8]. In other words, meeting the Paris temperature targets necessitates turning existing fossil fuel investments into stranded assets and fossil fuel reserves into stranded resources. The concept of "stranding" or "stranded assets" has been explored broadly in extant literature, from environment-related risk exposure of coal assets [9] to "unburnable fossil fuel deposits" such as oil, gas, and coal and the risk of stranded assets [10, 11].

Bos and Gupta [12] define stranded assets as "assets that lose economic value well ahead of their anticipated useful life, whether that is a result of changes in legislation, market forces, disruptive innovation, societal norms, or environmental shocks" p. 1 and stranded resources as "resources which are considered uneconomic or cannot be developed or extracted as a result of technological, spatial, regulatory, political or market limitations, or changes in social and environmental norms" p. 2. On the other hand, Caldecott et al. [13] define stranded assets as those assets which "suffer from unanticipated or premature write-offs, downward revaluations or [conversion] to liabilities" p. 11. Policymakers and experts concur that this transition should be managed proactively and pragmatically because if done haphazardly, it could perpetuate the techno-institutional complex of "carbon lock-in" and path dependency, thus making future transitions difficult [14–21]. On the other hand, if variable renewable energy resources like solar and wind electricity is introduced in significant quantities and not correlated exactly with peak load, it may create a unique challenge like the infamous California ISO's "duck curve" shown in **Figure 1**. How should the energy sector respond?

This chapter is structured as follows. Section 2 discusses digitalization solutions and business model innovations and presents moral arguments for supply- and demand-side energy solutions, including sensors, meters, higher efficiency devices, and energy auditing, including measurement and verification strategies that can be utilized to improve energy management. Specifically, using ML (machine learning- and (AI) artificial intelligence solutions to support (a) tackling stranded assets in

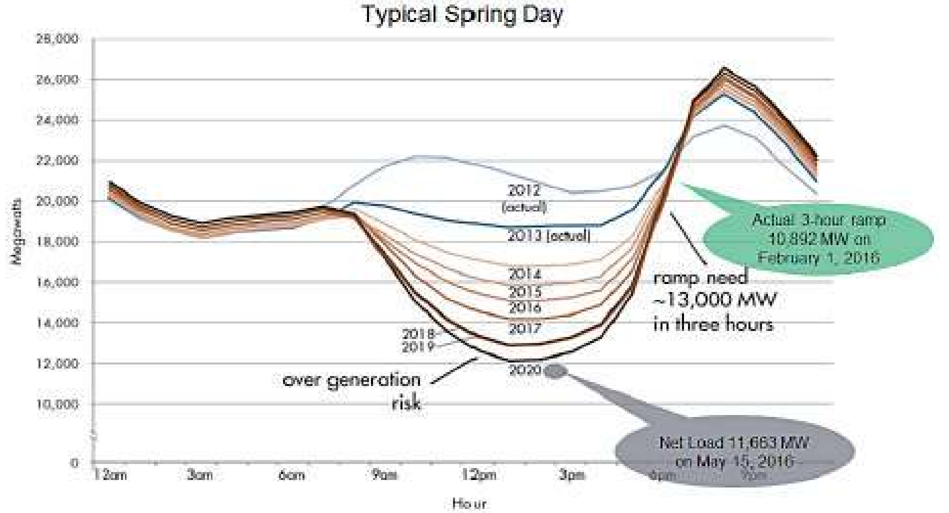

Figure 1.
California ISO's "duck curve." Source: CAISO (2014).

the transition to a low-carbon economy (b) real-time measurement of energy data, (c) manage data gathering and monitoring, (d) and proactively and accurately analyze the data gathered to detect changes in supply-demand imbalances and improve the situation promptly. Section 3 reviews the risks of stranding and identifies distinct opportunities for ML and AI applications in the energy sector. Section 4 emphasizes the impact of stranding risk factors on oil, gas, and coal resources and how this translates into the concept of "unburnable fossil fuel deposits." Section 5 discusses how advances in ML and AI techniques might help tackle the risks of stranded carbon assets, and Section 6 concludes.

2. Leveraging digitalization and business model innovations for energy management

Today's modern cities are sprouting with new industrial buildings and residential complexes. The consensus is emerging that dramatic growth in distributed renewable energy, and digitalization in economy and innovations, two megatrends of the twenty-first century, are critical strategies for climate change mitigation and changing the greenhouse gas (GHG) emission trajectories. Yet, while the electric power system is in transition, many of the vital power system challenges which confront governments and businesses, like access to a cleaner, more resilient, reliable, and affordable electricity, remain underfunded and unresolved. The increased deployments of energy management applications across the transportation, buildings, and industrial sectors, for example, reduce the cost of operation and consumption, lower energy losses, increase grid reliability, improve electric power production from carbon-free sources, and alleviate investment inefficiencies that could cause an energy-efficiency gap [22–24]. The continued growth of the fluctuated distributed generations (such as solar photovoltaics, wind turbines, electric vehicles, and energy storage systems) may perturb the network and create voltage drop/rise problems and in severe conditions, blackouts.

In a highly electrified economy with high shares of variable solar and wind electricity systems, reducing systemic mismatches between the generation and energy demand assets in an efficient manner requires investments in smart energy management systems. Energy management systems consist of two main categories: (a) supply-side devices from the electric utility-side used to manage the fluctuation of the load demand such as substations, and (b) the demand-side management devices used to manage energy consumption and meet the available power from the generation side [25–28]. Substations encompass transformers, switchgear, and protection, control and automation systems, and connect parts of the electric grid that operate at different voltage levels and managing these multidirectional power flows while ensuring reliability and security is critical as the share of decentralized and renewable energy increases. The rise of smart energy management systems, including ML, AI, big data, smart sensors, and the Internet of Things, is a boon not only to the electric power industry—especially in reducing operational costs and carbon emissions—but also the energy transition. For example, opportunities for leveraging digitalization for business model innovation in smart energy management and the corresponding implications for the power sector are substantial and untapped [29, 30].

Energy management is subject to barriers and limitations, which can delay its full market integration. These barriers include high cost of system implementation, inflexible fixed-price electricity tariff system and rate design, aging network's infrastructure, and the need for bidirectional power flow, which is ideal for an intelligent grid network. As a result, energy management continues to have a prominent role in decarbonization. Using ML algorithms and AI optimization models, utilities and system operators can apply optimal dynamic pricing and energy storage resource to improve the management of the "duck curve" phenomenon. For example, Sheha et al. [31] applied game-theoretic models to show that leveraging a combined effect of dynamic pricing profiles and distributed electrical energy storage can help flatten the duck curve, thus solar energy can be increasingly added on the grid without resulting in grid failure. The duck curve problem arises when increasing solar penetration on the grid creates a dip in net load in the middle of the day as solar generation peaks and wind electricity is low, followed by a significant rise in peak in residential demand at sunset as, without any form of energy storage, solar electricity rapidly subsides, and customer consumption increases as citizens get home from work/school thus necessitating significant ramping of thermal generators [24]. **Figure 1** shows California Independent System Operator's (CAISO) widely known "duck curve" (**Figure 1**) [32]. Besides California, the "duck curve" phenomenon also occurs in energy markets with high solar electricity penetrations such as Italy, Germany, Hawaii, and others.

To eliminate the risk of over-generation and possibly, alleviate the "duck curve" problem, implementation of long-term solutions focusing on distinct opportunities for ML techniques, including distributed solar coupled with storage technologies and smart energy management, are emerging in various energy markets. At stake, according to Guidehouse Insights (formerly Navigant Research), is $278 billion in annual global market for the deployment of commercial and industrial (C&I) energy as a service (EaaS) solutions by 2028 [33].

3. The risks of stranding in the energy sector

The intergenerational issues associated with climate change identifies it as an externality associated with carbon dioxide and other GHG emissions because it involves costs that are borne by future generations who have not created the emissions [34–38]. Climate change economists have introduced the concept of "social costs of carbon," which externalizes the externalities of these emissions by denoting the damages caused by them with a monetary value [35, 39–41]. It is for this reason that climate policy experts have advocated for a carbon price to achieve the "right price" as well as incentivize the investments in low-carbon technologies. Furthermore, from a policy, equity and regulatory point of view, scaling the deployment of low-carbon energy technologies inspires innovation in technological development, diffusion, transfer, and discourages the holding of dirty exhaustible assets (fossil fuel reserves) [42, 43], which are prone to becoming stranded due to perfect substitution, and disproportionately impact low- and moderate-income communities.

The risks of stranding of assets are likely to occur during the transition to a green economy. As van der Ploeg and Rezai [17] suggest two conditions are necessary for this transition to occur: (1), the unexpected future changes in the conditions likely to affect the economics of fossil fuel assets, such as customer demand, the social cost of carbon that values the climate externalities, and equity and efficiency considerations, must be present; (2) the cost of shifting around "the underlying capital stocks in the carbon-intensive industries to productive use elsewhere after the energy transition" must be too prohibitive or impossible to meet. Expectations about stranding carbon-intensive assets can occur due to sudden policy change, a breakthrough innovation in renewable energy technology such as energy storage batteries, which can lead to the stranding of fossil fuel-based financial assets since they directly pose a threat to the sustainability of the coal, oil, and gas-based business model.

With ML and AI techniques, energy operators can foster better short-term and long-term forecasting to improve electricity scheduling and integrated system planning, respectively. This would enable the utility operators and system managers to reduce their reliance on polluting, exhaustible fossil assets as well as proactively manage increasing amounts of distributed, low-carbon, variable energy sources like solar and wind energy. Additionally, the ML-AI-driven energy forecasts can provide accurate and optimal management of power grid fluxes to help operators proactively match demand-supply imbalances, manage uncertainties, as well as understand where, when and how many solar power systems [44, 45] and wind generation plants [46] should be built.

However, much of these forecasts employ domain-agnostic techniques, in which domain-specific scenarios are often less applied. For this reason, ML and AI algorithms of the future must incorporate weather-related innovations in climate science and weather modeling techniques in order to improve parametric and nonparametric estimates of both short- and long-term forecast uncertainty, for example, of variable generation and electricity demand [44, 46–49]. For example, using a novel deep learning framework that combines wavelet transforms, stacked autoencoders, and long-short term memory, Bao et al. [50] produced stock price forecasts that outperform other similar models in both predictive accuracy and profitability performance. This notion can be extended to aid electricity demand forecasts that optimize intraday and day-ahead levelized cost and levelized avoided cost of electricity generation resources that minimize GHG emissions. More broadly, in the transition from the incumbent centralized electricity network to a distributed model that is underway, driven by the rapid growth of DERs, understanding the domain value of improved forecasts (e.g., to model electricity load in rural microgrids) across the quartiles of electricity market operation, matching of supply-demand imbalances, network control, and governance and administrative networks [2, 51] is an exciting challenge for ML and the debate on stranded assets.

4. Investments, stranding risk factors, and unburnable fossil fuel deposits

Going by Bos and Gupta [12] and Caldecott et al. [9]'s definition, stranded assets and stranded resources manifest in two main ways (1) devaluation through the unburnable fossil fuel resources, which must be kept in the ground to keep the long-term global temperature target to below 2°C above pre-industrial levels [4], and (2) premature retirement of exhaustible fossil capital assets due to climate policies, including the optimal social cost of carbon in the form of a carbon price [40]. **Figure 2** shows the US annual electricity generating capacity additions and retirements from oil, gas, and coal power plants.

In the US Energy Information Administration (EIA) Annual Energy Outlook's Reference case, natural gas-fired combined-cycle generation capacity will continue to be added steadily through 2050. Significant retirements of electric generation capacity, mostly from coal, occur by 2025, while approximately 117 GW of new wind and solar capacity additions could occur between 2020 and 2023 [52]. This means that without investing in heat rate improvement technologies by 2025 to increase their efficiency, coal-fired generation systems must retire to comply with the affordable clean energy (ACE) rule or become stranded assets. The AEO2020 Reference case also shows that the low cost of natural gas prices significantly contributes to the retirements of coal-fired and nuclear power plants by 2025. Diverse policy efforts, notably increasing state RPS targets, net metering policies, and declining capital cost profile of solar, are expected to incentivize and accelerated its growth through 2050 by making the investment case for widespread solar energy deployment attractive to investors, particularly when utility-scale and small-scale applications are considered. **Table 1** summarizes the seven main drivers of stranding and the different aspects of stranded resources and assets.

According to the Potsdam Climate Institute, to meet the Paris Agreement of a temperature target below 2°C of global warming with the aim to limit it to 1.5°C, the global carbon budget of the total volume of CO_2 emissions permitted by 2050 is 886 $GtCO_2$ [74]. However, more than a third of this carbon budget has already been used up from burning fossil fuels, leaving a budget of around 565 $GtCO_2$. In the case of a 1.5°C temperature limit or even lower, this budget would be drastically contracted. It is for this reason that national, state and local governments must prioritize low-carbon transformations; for instance, (i) ramping up renewable energy over the next two decades, (2) switching from oil to less carbon-intensive gas [5, 15, 25, 42, 48, 55, 75–77], and (3) keeping large global deposits of

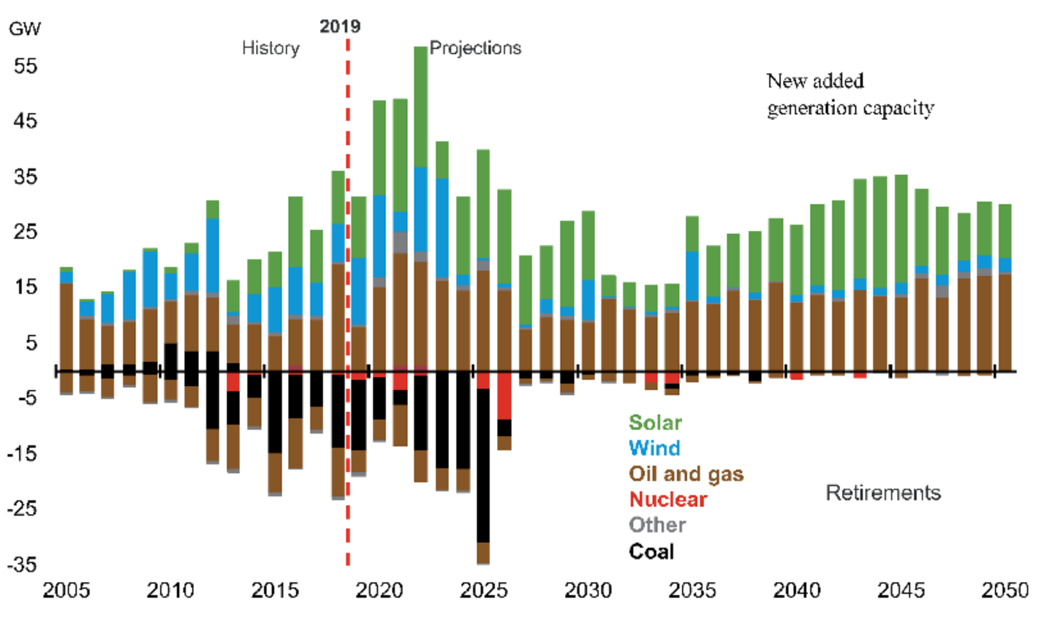

Figure 2.
Annual oil, gas, and coal electricity generating capacity additions and retirements. Source: EIA (2020).

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Type of stranding	Nature of asset	Cause of stranded asset	Stranded resource	Liability	References
Economic	Viable projects receive investment (e.g., growing biofuels in deforested lands)[a]	Increased market competition affects investment in the asset (e.g., falling oil prices leads to cuts in oil exploration investments)	When it becomes uneconomical to extract/convert the resource due to low demand	Premature stranding costs (e.g., decommissioning and phase-outs costs)	[10, 53–56]
Technological	New technological breakthroughs (e.g., hydraulic fracturing, CCUS, and solar geoengineering like injecting sulfate aerosols into the stratosphere)[b]	New technologies and disruptive innovations render old technologies obsolete	Slow technological learning to access the resource (e.g., deep-sea exploitation and exploration)	Liability when technology becomes obsolete or dangerous	[57–61]
Political	The political climate is conducive for resource exploitation	Geopolitical changes like sanctions may affect assets (e.g., The Trump administration sanctions against Huawei affected Chinese oil/gas contracts)	Political strife or civil war inhibits resource exploitation	Liabilities levied against governments or organizations for (short-term) policies (e.g., aid agencies for export credits on polluting industries)	[9, 12, 62, 63]
Policy/legal	Policies and laws allow consumption, contracts, leases, and intellectual property rights/patents	New legal regime leads to asset retirement or phasing out (e.g., nuclear phase-out)	Policies or laws may restrict resource extraction or conversion (e.g., moratoria)	Pareto improvement; Liabilities for the premature stranding of investments due to policy changes (e.g., trade agreements)	[15, 64]
Spatial	The asset can be exploited	Resource depletion; water scarcity	The resource is remote (e.g., inaccessible gas or solar resource)	Liabilities for clean-up costs (e.g., Superfund clean-up costs for contaminated pollutants)	[65–67]
Social	Communities or consumers prevent the use of the asset (e.g., NIMBY ("not in my backyard") protests)	A community or consumer protests lead to its ban (e.g., Keystone Pipeline XL protests)	A community or consumers prevent the use of a resource (e.g., local fracking bans)	Compensation for resource damage (e.g., US Deepwater Horizon BP oil spill environmental damages, Nigeria's Niger Delta oil spills accidents)	[68–70]

Type of stranding	Nature of asset	Cause of stranded asset	Stranded resource	Liability	References
Ecological	Economic benefits are greater than the ecological impacts.	Ecological considerations (e.g., climate change) outweigh economic arguments.	Ecological effects inform non-use decisions of resource (e.g., large hydro dams)	Insurance or costs of adaptation borne by an investor Punitive damages incurred as injunctive relief	[56, 71–73]

[a] *Increased efficiency could create higher overall demand referred to as the Jevons paradox. For example, a shift to electric vehicle model may lead to the rebound effect, resulting in increased vehicle miles travelled, and overall rise in GHG emissions [54, 56].*
[b] *New technological breakthroughs like carbon capture, utilization and storage (CCUS) innovations can be used to extract CO_2 from power plant exhaust and industrial processes.*

Table 1.
The different aspects of stranded resources and assets.

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Total proved coal reserves at the end of 2019			Total proved oil reserves at the end of 2019			Total proved gas reserves at the end of 2019		
Country	**Reserves (million tons)**	**% World**	**Country**	**Reserves (billion barrels)**	**% World**	**Country**	**Reserves (trillion cubic meters)**	**% World**
The United States	249,537	23.3%	Canada	170.8	9.8%	The Russian Federation	38.0	19.1%
The Russian Federation	162,166	15.2%	Venezuela	303.8	17.5%	Iran	32.0	16.1%
Australia	149,079	13.9%	Kazakhstan	30.0	1.7%	Qatar	24.7	12.4%
China	141,595	13.2%	The Russian Federation	107.2	6.2%	Turkmenistan	19.5	9.8%
India	105,931	9.9%	Iran	155.6	9.0%	The United States	12.9	6.5%
Indonesia	39,891	3.7%	Iraq	145.0	8.4%	China	8.4	4.2%
Germany	35,900	3.4%	Kuwait	101.5	5.8%	Venezuela	6.3	3.2%
Ukraine	34,375	3.2%	Saudi Arabia	297.7	17.1%	Saudi Arabia	6.0	3.0%
Poland	26,932	2.5%	The United Arab Emirates	97.8	5.6%	The United Arab Emirates	5.9	3.0%
Kazakhstan	25,605	2.4%	The United States	68.9	4.0%	Nigeria	5.4	2.7%
Turkey	11,525	1.1%	Libya	48.4	2.8%	Algeria	4.3	2.2%
South Africa	9,893	0.9%	Nigeria	37.0	2.1%	Iraq	3.5	1.8%
		92.8%			90.1%			84.0%

Source: BP Statistical Review of World Energy 2020 [78].
Notes: The total world proved coal, oil, and gas reserves at the end of 2019 were 1,069,636 million tons, 1735.9 billion barrels, and 198.8 trillion cubic meters, respectively. The total proved coal reserves include both anthracite and bituminous reserves and sub-bituminous and lignite reserves.

Table 2.
Global reserves of coal, oil, and gas.

coal, oil, and gas reserves "in the ground" (**Table 2**) [11, 13, 79]. This call has led to the "keep fossil fuels in the ground" initiative, "fossil fuel divestment" campaign, and "unburnable carbon" resistance movement, as a way to compel companies which are active in hydrocarbons or with high coal, oil, and gas reserves in their portfolios to reinvest elsewhere [17, 63, 79–84].

Table 2 shows the top 12 countries for each of the three fossil fuels. These coal, oil, and gas reserves represent 92.8%, 90.1%, and 84%, respectively, of the total global, proved reserves at the end of 2019 [78]. McGlade and Ekins [11] have computed a breakdown of the socially optimal distribution of stranded carbon assets that must be kept in the ground to meet the Paris Agreement temperature targets. They find that to have "a better-than-even chance of avoiding more than a 2°C temperature rise, the carbon budget between 2011 and 2050" must be kept at "around 870–1240 $GtCO_2$" p. 187. This translates to approximately one-third of global oil reserves, half of the global gas reserves, and over 80% of global coal reserves of unburnable fossil fuels. **Figure 3** summarizes the regional distribution of these unburnable reserves. These figures are in line with other estimates of the stranded coal, oil, and gas assets by other experts and organizations, that must be kept in the ground, to meet the 2°C Paris commitments [5, 10, 74, 85, 86]. However, while in the end, all carbon must be phased out, less-carbon intensive energy carriers like gas might continue to operate as a "bridging fuel" to the carbon-free economy, in tandem with renewable energy. When considering short- and long-term nature of technology rebound effects, path dependency in policymaking, and carbon lock-in in different markets [16, 20, 87–92], adopting adaptive strategies, incorporating technology transfer, and incentivizing international collaboration in energy research, are vital stratagems for managing the distributional impact of this energy transition process as well as upstream value chain requirements (such as future nuclear baseload supply and renewables-based hydrogen generation).

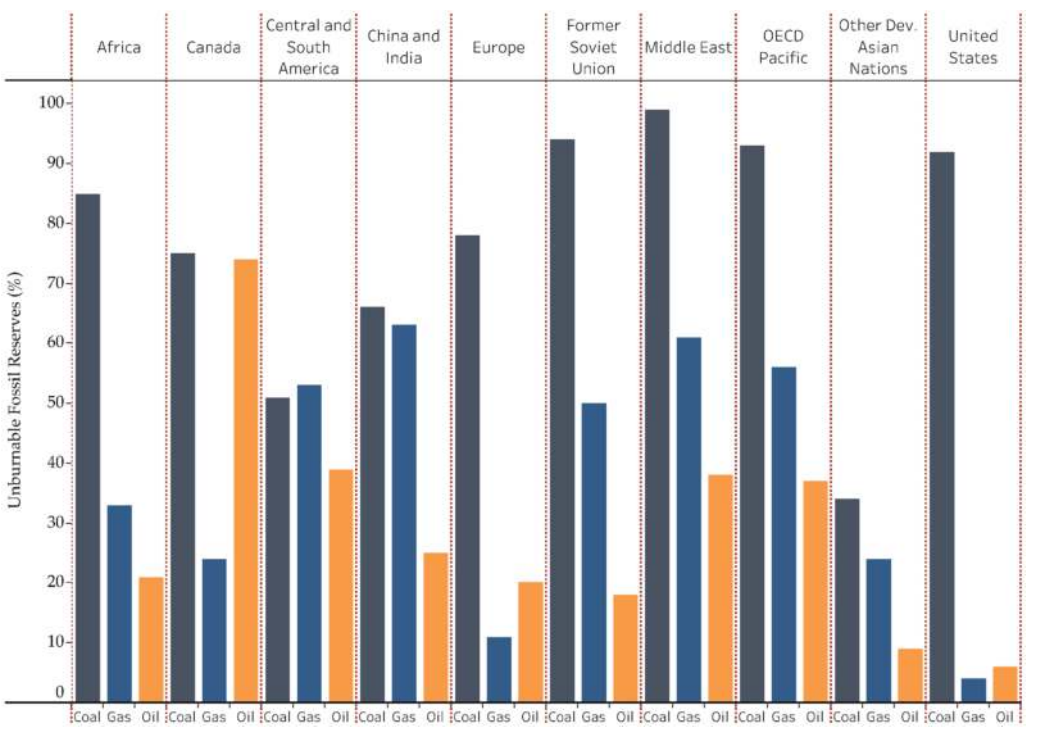

Figure 3.
*Percent of regional distribution of unburnable fossil reserves before 2050 for the 2°C scenario—data from McGlade and Ekins [11], **Table 1**.*

5. Mitigating stranded assets risks using ML and AI techniques

Returning to physical and financial carbon assets at risk of being stranded, ML and AI techniques can provide appealingly pragmatic Pareto-optimal solutions for mitigating stranding risks among different policy aspects instead of using scalarization, thereby creating a balanced transition to lower-carbon technology [93–95]. What causes assets to strand? As discussed in Section 2, multiple factors, including economic, technological like disruptive innovation, political, regulation, spatial, and societal norms, or environmental shocks, can lead to asset stranding. Stranding is not just a loss in economic value but also an irreversibility of the investments. This means that if the investments wiped out is reversible and can be adjusted for other purposes such as retooling an obsolete coal power plant to be used as a hydro generation facility; then the assets have not stranded since they can be put to different profitable use [63, 80, 86].

With respect to the unburnable carbon, stranding occurs when coal, oil, and gas companies, who have already committed heavy capital investment in related infrastructures such as exploitation, exploration, and pipelines, become hit by a sudden drop in commodity prices, leading to the stranding of their capital stocks. This could also happen when a government establishes an unanticipated Pigouvian fee, promoted by Pigou in a seminal article [96], on GHG emissions to correct for the unpriced environmental externality, either via a carbon price [97, 98] or a market-based emissions cap-and-trade mechanism [99]. This can have negative consequences for the market valuation of the upstream and downstream fossil fuel-based businesses and producers of electricity, leading to forced write-offs of their carbon assets [21] or their capital stocks getting stranded. For example, following the passage of the Powerplant and Industrial Fuel Use Act (FUA) in 1978 in response to the Arab oil embargo of 1973, a significant shortage of natural gas occurred, leading to a drop in natural gas-fired generation capacity additions. The unintended consequence of this policy-driven change in the national electricity generation mix was a shift to coal-fired generation capacity in the intervening years, leading to a rise in energy-related long-term carbon emissions.

In recent years, research shows that ML and AI are broadly powerful tools for technological progress that can be applied with a high impact in mitigating the transition to low-carbon technologies, especially in tackling the problem of stranded assets in the electricity sector. Power generation and demand forecasting is one area in which ML and AI techniques can improve policy vagaries and uncertainty about future demand, thereby mitigating the risk of stranding [17]. Below are the 10 distinct opportunities for ML and AI applications in the energy sector that include:

1. Electricity scheduling and dispatch: Improving electricity scheduling and dispatch mechanisms using ML and AI tools amidst increasing variable DER generation, storage, and flexible demand.

2. Energy data analytics and informatics: Using ML supervised models, e.g., that employ regression-based techniques on cellular network data, to generate information about low-data settings and determine where electricity power lines can be placed in regions unmapped, and help improve energy access [100].

3. Energy materials research: Applying ML, AI, optimization techniques, and physics to better understand the science of energy material's crystal structure, to accelerate materials discovery for solar fuels that improves harnessing of energy from variable natural resources [101].

4. Natural gas methane detection and prevention: Employing ML and AI techniques to detect and prevent the leakage of methane from natural gas pipelines and compressor stations.

5. Nuclear fission and fusion: Application of ML and deep networks to speed up inspection of nuclear power plants and help design next-generation smart, modular nuclear reactors [102, 103].

6. Solar PV design and innovations: Using ML techniques to design controllable movable solar panels that maximize electricity production, for example, in bifacial solar modules and dual-orientation racking techniques [53, 104–107].

7. Solar PV technical and economic potential estimation: Using ML to help estimate technical and economic potential of rooftop solar PV, e.g., by optimizing Light Detection and Ranging (LIDAR)-Geographic Information Systems (GIS) imagery-rendering of size and location data for rooftop solar panels [108, 109] .

8. Wind power management and monitoring: ML-driven condition monitoring (such as dimensionality reduction algorithm like Principal Component Analysis—PCA) of wind turbine blades, including optimization of blade fault detection, power curve monitoring, and temperature monitoring [110, 111].

9. Integrated transportation planning: Using AI and ML to improve vehicle engineering, shared mobility, and shift to lower-carbon options, like rail. In the long-term, ML and AI applications can support integrated intelligent infrastructure through planning, maintenance, and operations to make transportation more efficient though the GHG reduction, provide better demand forecasts, and support smart transit policy efforts such as autonomous vehicles, alternative fuels and electrification (e.g., electric vehicles, and vehicle-to-grid algorithms), and predicting battery state and degradation rate using supervised learning techniques [112–116].

10. Urban energy planning: With ML and AI applications, available building[1] energy use data can be extrapolated to predict energy use at the city level. Furthermore, ML is uniquely capable of supporting improvements in "smart energy frameworks for smart cities" [25], including building codes, informing policymakers about utilizing urban rooftops for solar PV electricity generation [55, 108], retrofitting strategies using automated performance control [117], public-private partnerships to improve low-and moderate-income (LMI) stipulations and equitable electricity access [15, 64].

The above list is by no means exhaustive. The transformation to a low-carbon economy is occurring at an expanding rate. The technical innovations accompanying these carbon-free energy sources such as solar, wind, hydro, and geothermal energy is driving down the cost of these technologies as production increases and knowledge accumulation results from learning by doing. As a result, they are yielding substitutes for coal, oil, and progressively rendering coal, oil, and gas capital stock obsolete. It is

[1] The IPCC classifies mitigation actions in buildings into four categories: carbon efficiency (switching to low-carbon fuels or to natural refrigerants); energy efficiency (reducing energy waste through insulation, efficient appliances, better heating and ventilation, or other similar measures); system and infrastructure efficiency (e.g. passive house standards, urban planning, and district cooling and heating); and service demand reduction (behavioral and lifestyle changes).

expected that as this shift continues, new opportunities for ML and AI applications will become available, including in modeling consumer behavior and facilitating sustainable behavior change energy consumption action [3, 65, 118, 119], estimating and predicting the marginal emissions of residential energy utilization and thermal comfort in buildings in real time, on a scale of hours [57, 118], and game-theoretic modeling and design of socially beneficial energy policies like social norms, public opinions, stakeholder engagement, and education efforts [120–122]. Other breakthrough innovations might displace fossil fuels leading to stranding, and creating opportunities for ML-based electricity pricing techniques and rate design to set dynamic pricing of carbon, electricity, and consumer choice [1, 123–127], and multi-objective optimization to compute Pareto-optimal solutions for climate engineering, climate informatics, and solar geoengineering [58, 128–130]. There is a possibility that these technological innovations could create a sudden improvement in market evaluation of the renewable energy industries, while some assets of related carbon-intensive industries become stranded due to obsolescence, write-offs, or retirements.

6. Conclusion

Following the passing of the Paris Agreement on climate change, nations committed to keeping the global temperature below 2°C. Achieving this temperature target means coal, oil, and gas producers face stranding more than 80% of all these proven fossil fuel reserves and existing investments becoming stranded assets. These threats lead policymakers and market analysts to conclude that market evaluation and capital investments of some of these carbon-intensive firms risk being stranded, unless they fundamentally change their business models per the risk of asset stranding, to cushion themselves from unanticipated economic, technological, political, regulatory, spatial, social, and environmental changes, resulting in cheap renewable substitutes for coal, oil, and gas. A pragmatic and proactive response by governments is urgently required in the form of NDCs and climate policies to guide this transition, and that puts nations on a sustained path to the 1.5 or 2°C "carbon budget." Such a process should avoid a disruptive and unorderly energy transition and macro shocks. Using ML and AI techniques to tackle the risks of stranded carbon assets and related infrastructure can enrich and inform this praxis. Stranded assets are not new in the energy sector; the physical impacts of climate change and the transition to a low-carbon economy have generally rendered redundant or obsolete electricity generation and storage assets. Low-carbon electricity systems, which come in variable and controllable forms, are essential to mitigating climate change. These systems present distinct opportunities for machine learning and artificial intelligence-powered techniques, making their applications prominent.

Sen and von Schickfus [62] calculate that €1.61 billion of security reserve or €13.38/MWh subsidy, is required to compensate coal energy assets in Germany at the risk of becoming stranded. Given the threats of sudden changes in the stringency of carbon policies and related abrupt repricing or retirement of fossil fuel assets, they also find that investors generally do care about stranded asset risk, but that they also expect to be financially compensated for stranded assets. This analysis highlights the threat of stranded asset risk in the coal industry and the need for understanding the interaction between policymaking and investors' expectations. For example, the International Renewable Energy Agency (IRENA) [131] estimates that to meet the Paris Agreement's 2°C temperature target, $1.9 trillion in electricity generation assets would be stranded after 2030. The report concludes that stranding will disproportionately affect $7 trillion in upstream energy infrastructure, of which three-quarters are in oil production. Institutional investors must tap ML and AI techniques ML to improve energy planning and system efficiency (e.g., detect and prevent the leakage of methane from natural gas pipelines, speed up inspection of nuclear power plants, and improve electricity scheduling and dispatch mechanisms). Given the vital role of the energy sector and its interrelation with the rest of the economy, using ML and AI to tackle stranded electricity assets is emerging as a cost-effective derisking strategy. Stranding and the risk of stranded carbon assets is a growing challenge requiring an interdisciplinary approach that brings together ideas from engineering, economics, and policy fields, as well as quantitative opportunities of ML, AI, optimization, and dynamical systems, to address interpretability, uncertainty quantification, and integration questions.

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